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ABSTRACT

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AN EXAMPLE OF THE APPLICATION OF GENERALIZED INFORMATION SYSTEMS CONCEPTS TO THE QUANTIFICATION OF INFORMATION IN A DECISION SYSTEM:

THE EXAMINATION OF QUANTIFIED INFORMATION FLOW IN AN INDUSTRIAL CONTROL PROBLEM

by

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PREFACE

This report is the result of research in generalized information systems supported in part by Grant Number GN 534.1 from the Office of Science Information Service, National Science Foundation, to the Computer and Information Science Research Center, The Ohio State University.

The Computer and Information Science Research Center of The Ohio State University is an interdisciplinary research organization which consists of the staff, graduate students, and faculty of many University departments and laboratories. This report presents research accomplished in cooperation with the Department of Computer and Information Science.

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INTRODUCTION

This research study is based on an application of concepts derived from the Yovits-Ernst Model[1] for a generalized information system. These concepts and their implications are applied to a management decision model for a hypothetical production control problem.

The purpose of this investigation is to demonstrate that the theory of the Yovits-Ernst Model can provide a valid analytical base from which a precise quantification of the flow of information through a decision system can be achieved. An additional goal is to formulate and to investigate some of the overall implications that may result from such a quantification.

One of the key features underlying the approach taken in this research effort is that information is used in order to make decisions. When viewed as a resource for decision making, information may then be defined as _data of value in decision making_. Consequently, the amount of information contained in a set of data is a function of the amount of change this set makes or is capable of making in the outcome of the decision for which it is to serve as a resource. The amount of change in the outcome of a decision is observable, measurable, and, therefore, quantifiable. Thus information may be quantified in terms of its quantitative effect, or potential quantitative effect, on a decision outcome. Also, since it is reasonable to speak of a minimum observable change in the results of a given decision, it is also then reasonable to call that amount of information which is capable of effecting this change a _quantum of information_.

[1]The Yovits-Ernst Model is described in detail in (8).

The problem setting consists of a hypothetical production control decision-making environment in which a production manager must determine, at the beginning of each production period, the level at which a firm is to produce its single product for that particular period. The production manager has available as a resource an "information system" which provides him with information about those factors that the production manager intuitively feels he needs to know in order to make the necessary decision. Clearly, the problem setting is one with dynamic decision theory characteristics in that the production manager is required to make a distinct decision at discrete points in time; furthermore, in a realistic production control environment, it is not unlikely that the outcome of a given decision will affect subsequent decisions.

A simulation model is constructed to serve as the vehicle for experimentation. It must be pointed out, however, that whereas simulation experiments usually attempt to evaluate alternatives via experimentation with a model of a complex system that actually exists, here the simulation model is a model of a hypothetical situation and is, therefore, actually the "real world" upon which experimentation and analyses are performed. As a result, of course, no statement concerning a positive correlation with an actual production control environment can be made. (But then such a statement would clearly be outside the purposes of this study.) It will be argued, however, that although the experimentation and analyses are performed in an artificial domain, the insights and the implications derived are real in that they offer viable correlations and contributions toward the quantification of information flow in real-world decision systems.

1. THE YOVITS-ERNST MODEL AND THE HYPOTHETICAL PRODUCTION CONTROL PROBLEM

Since the model of a generalized information system provides the basic framework from which the concepts to be discussed in this paper were taken, it will be useful to describe this system in some detail in order to provide the background necessary for understanding the remainder of the paper. The generalized model is depicted schematically in Figure 1.

The system is comprised of four essential functions. These include the Information Acquisition and Dissemination function (IAD), the Decision Making function (DM), the Execution function (E_x), and the Transformation function (T). Virtually all situations involving the flow of information can be described by this model. These situations would include the use of information by the research scientist or the development engineer, management of a large corporation, command and control of a military engagement, or such relatively straight-forward and simple activities as the switching on or off of a thermostat-furnace system.

Personal decision-making problems are described by Figure 1. It is not even necessary that the decision-making process be a logical one. This model is applicable when decisions are completely irrational, as may frequently be the case. Each of the four functions is seen to collect, store, operate, and disseminate.

In any realizable and operational system, all the indicated functions must be present, and they must be considered together in order to understand information flow or in order to establish principles, relationships, or guidelines for information flow. Just as in the analysis of any system, suboptimization or consideration of the functions independently may yield misleading or incorrect results.

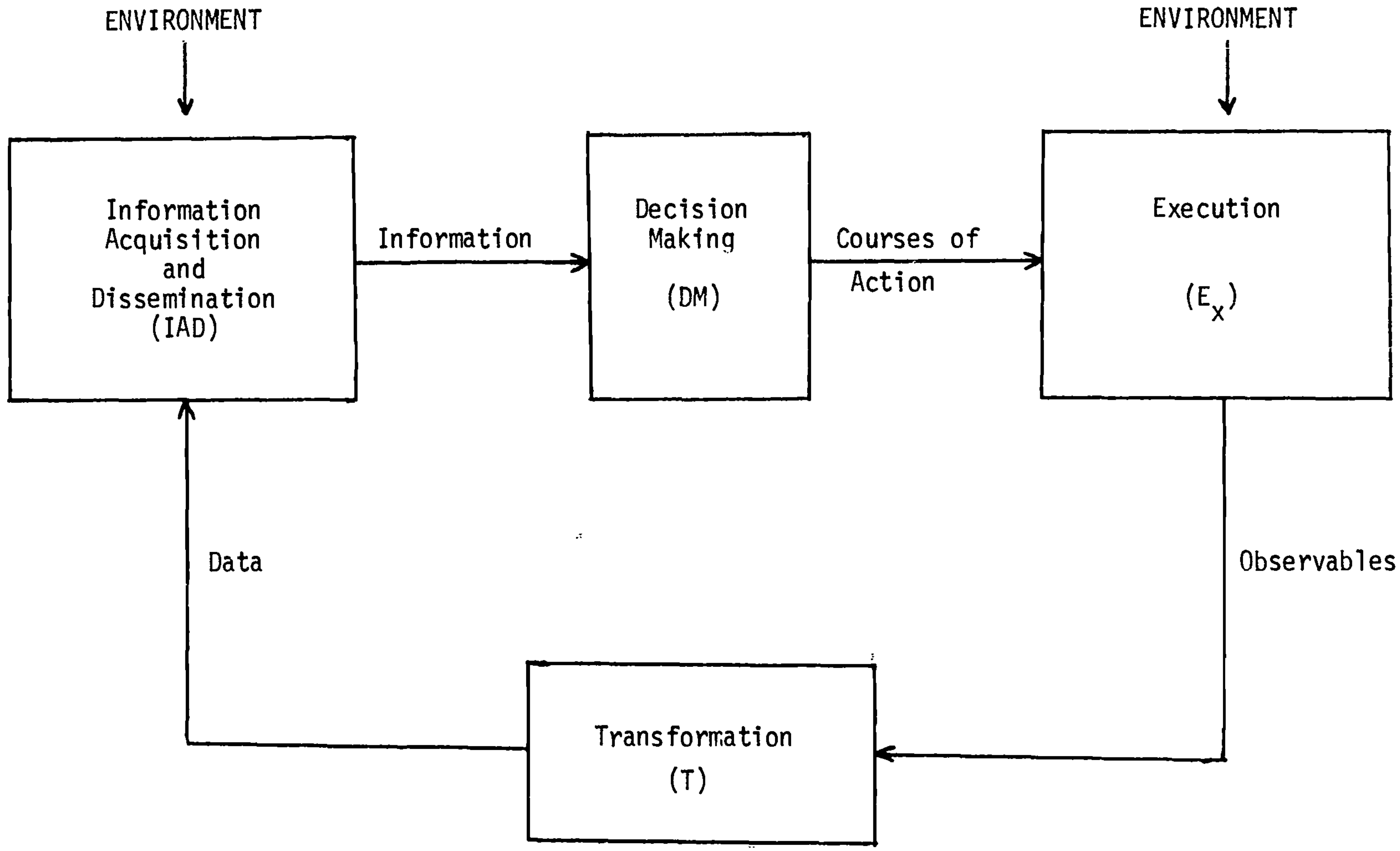

Figure 1. GENERALIZED INFORMATION SYSTEM

In particular, the DM function is a most important one and is established as the key consideration in the entire information flow process. The DM function represents any system component accepting an input from the IAD and providing an output to the E_x. The DM may be an individual person, an organization, a man-machine system, or simply a machine system. In all of these cases, the DM transforms information into courses of action which are subsequently "executed" into observable actions. The input to the DM is information, some of which may be stored or held in memory. The DM makes decisions on the basis of the information available at some particular time. However, it is assumed that decisions are always made individually, serially, sequentially, or in parallel and, of course, the decision-making process may be delayed. This is usually the case when more information is necessary. But, at any rate, the decision maker is responsible for the generation of observable actions and will eventually make decisions that will lead to these actions.

1.1 The IAD

The Information Acquisition and Dissemination device collects data from the external economic environment and data that are transformations of the observable outcomes of previous decisions. More generally, the IAD interfaces with the "real world" and, therefore, has at least some possibility of collecting data about those phenomena that will ultimately affect the outcome of the next decision. At any rate, the IAD operates on the collected data by filtering, weighing, analyzing, restructuring, etc., and eventually emits two signals x_t and y_t to the DM. These signals are time-dependent predictions about the state of the external economic environment and about the state of the transformation space consisting of all possible configurations of the feedback data.

Notationally, define E to be the external economic environment space (i.e., the set of all possible states or configurations of the external economic environment) and R the transformation or result space (i.e., the set of all possible states or configurations of the feedback data). It is assumed that both E and R are finite sets of discrete states.

In this specific problem setting, it is assumed that the IAD analyzes all data and restructures it in terms of two indices: 1) a feedback data index $x_t \epsilon X$ where X is the set of signals about the result space R and 2) an external economic environment index $y_t \epsilon Y$ where Y is the set of signals about the environment space E. Generally, it would be feasible to think of x_t and y_t each as a composite index based on a function of several variables. For example, the value of the feedback data parameter x might be a function of inventory level, sales, labor situation, raw materials, etc.

The relationships governing the transformation of the collected data into information (i.e., the signals x_t and y_t) by the IAD can be made more precise if these phenomena, no matter how intuitive and abstract they might be, are interpreted as mappings from a space consisting of the true states of nature into a space consisting of signals about the true state. These mappings are said to be "information structures".[2] This seems quite compatible with the notion discussed previously concerning the fact that the IAD interacts with the true state of nature but is capable of emitting only its interpretation of that state. Furthermore, this notion also seems quite consistent with the truism that rarely is

[2] As discussed by Li in (6).

information emitted from an information system 100% correct. It is usually the case that there is a degree of uncertainty present concerning the correctness of the information; the source of this uncertainty, it would seem, is precisely the IAD's inability to interpret perfectly the true state of nature. However, for the sake of sensitivity analysis, it will be assumed that no uncertainty accompanies the signals disseminated by the IAD (i.e., the information structures to be discussed are assumed to be perfect interpreters of the various states of nature). If the information structure I_y is the mapping that relates the environment space E to the signal space Y and if I_x related the result space R to the signal space X, then Figure 2 schematically represents the activities of the IAD.

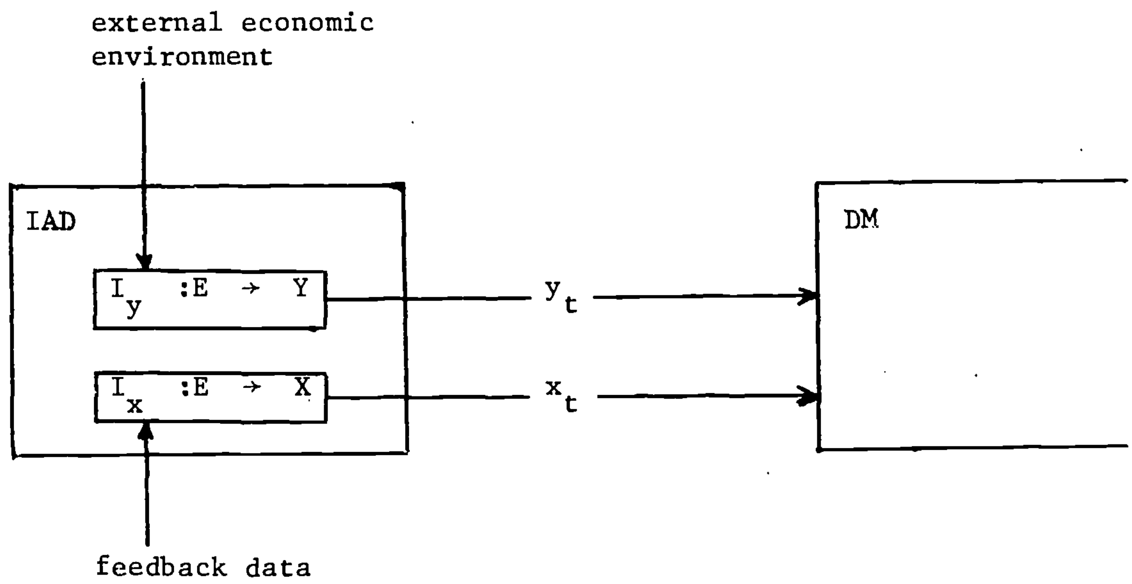

FIGURE 2.

1.2 The DM

At a given decision opportunity the decision maker (DM) has available timely information as a resource; hence, the input into the DM is information about the uncontrollable state of the external economic environment and the (relatively) controllable state of the result space. This information is in the form of the two signals x_t and y_t. The DM then utilizes these two time-dependent decision parameters to determine that production level q_t for the t^{th} production period that he believes will prove to be optimal (in the sense that given the state of nature indicated by the parameters x_t and y_t, then producing at level q_t will, according to the DM's conception of how these parameters are related, yield the maximum utility to the firm). This process occurs according to the relationships embodied in the DM's predictive model; that is, the DM has a conception (however intuitive it might be) about how the input parameters he receives are related to the predicted optimal production level. This phenomenon can be made precise by saying that a production function $f(x_t,y_t) = q_t$ constitutes the DM's predictive model.

It is worthwhile to point out that the DM may well have more than one predictive model at his disposal. In this instance, an alternate production function $g(x_t,y_t) = q_t$ would constitute such a model. At a given decision opportunity, the DM may utilize only one such predictive model. However, for a set of decision opportunities, the DM may, according to some predefined strategy, utilize both models at different points in time.

Upon calculating the predicted optimal production level q_t, this function value is then compared to the known production level

q^o_{t-1} for the last period. If we define $(\Delta q)_t = |q_t - q^o_{t-1}|$, then we shall assume that the DM deterministically decides to raise or lower the production level by $(\Delta q)_t$ as is necessary to reach q_t. Though we are restricting the discussion at this point to this single "identity decision rule," it is quite feasible that the DM has alternate decision rules available. For example, if the DM feels that the predicted optimal level has been on the conservative side, his decision rule might consist of altering the production level by $k(\Delta q)_t$ where k is some real number greater than 1; obviously, if the situation warranted it, a more complex function of $(\Delta q)_t$ could constitute the decision rule.

At this point it is clear that three things influence the actual decision-making process performed by the DM: 1) the information available (the input signals); 2) the predictive model used; and 3) the decision rule used. There is an obvious interdependence between (2) and (3) above, as is evidenced by the fact that, if the decision rule is fixed, the ultimate course of action decided upon is, in essence, completely determined by q_t, the output of the predictive model. A precise description of this "interdependence" is not, at this point, the purpose of this study. Hence, for the time being, it is sufficient to realize that together the DM's predictive model and the associated decision rule constitute a decision process that is essentially a mapping from an information space X x Y into an action space consisting of all the possible changes in the production level for the next period.

Figure 3 schematically portrays the DM.

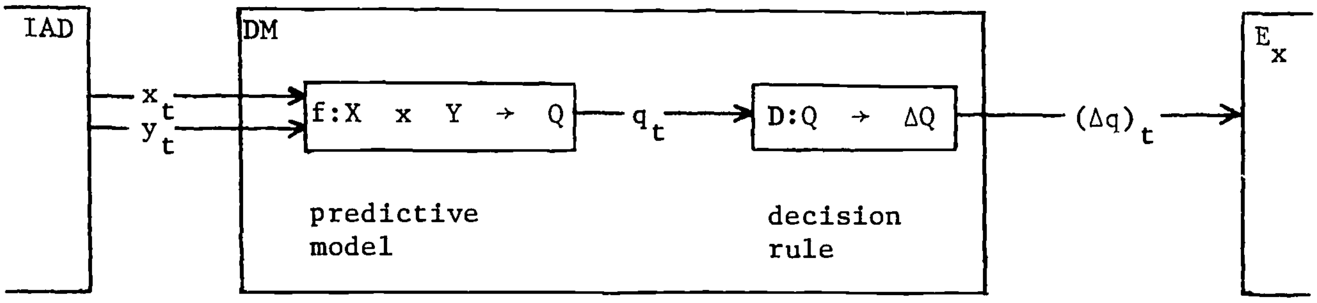

FIGURE 3.

It has been implicitly assumed that before this whole dynamic decision process began, the DM (or his consulting information scientist!) specifically determined that the information he needed as a decision resource at each decision opportunity is precisely the values of the parameters x_t and y_t (or, at least, the IAD's interpretation of these values). Hence, x_t and y_t constitute the decision parameters for the process. As is well-known, the precise determination of what parameters are relevant to a decision process is a formidable problem in itself that is outside the scope of this study. However, if these parameters are known, then the determination of which items in a set of data are relevant (that is, which items will ultimately be of value to the DM in the sense that they are capable of effecting a change in the observable outcome of the decision process) is precisely one of the purposes of this study. In view of this, it is worthwhile to note that the IAD should send to the DM only that information which the DM needs to make the decision; anything else would be irrelevant and/or redundant if it was not, in fact, potentially capable of influencing the observable outcome of the decision. Hence, the IAD (which most literature labels "the information system") should be designed according to the requirements of the decision-making situation at hand.

1.3 The E_x and the T Components

In the context of this problem, the Execution (E_x) component would consist of the physical production plant. This component of the system is charged with implementing the desired course of action decided upon by the DM. This implementation may take place perfectly (no uncontrollable environmental interference) or imperfectly (uncontrollable fluctuations of the environment intervene).

For the sake of simplifying the analysis, the Transformation (T) component, assumed to be fixed, perfectly transforms the observable outcomes of the decision into financial accounting data, utility data, or whatever. In reality, there may be many "transformers" performing this function: the firm's warehouse, sales office, personnel department, etc. Functionally, however, it is possible to think of this component as perhaps an accounting function where a team of accountants gather all the observable manifestations that occur as a result of the last decision and convert or restructure them into financial accounting data (or into utility measures of one sort or another if the firm's overall optimality criterion embodies subjective features that cannot be expressed in terms of dollars and cents). Also, it is noteworthy that the T component does no filtering; it sends the transformations of all observable results to the IAD.

2. QUANTIFICATION OF INFORMATION FLOW

In a realistic production environment there will be, dependent upon the current production level, a certain change in production such that below that change it will not be profitable for the firm to alter the production level-- for such reasons as the fact that the "set-up costs" are likely to outweigh any potential gain in revenue. More precisely, if this change in production for production period t is denoted by $(\Delta q)^*_t$, then the minimum profitable change is given by $(\Delta q)^*_t = h(q_{t-1})$ where q_{t-1} is the value of the production level for period t-1 and h is the function relating the two. This phenomenon provides the means necessary for establishing, for each decision parameter, that smallest quantum of information which is ultimately capable of effecting a change in the observable outcome of a decision. This unit of information will be called an "informon".

In terms of the decision parameter x_t, we can then define an x_t-informon as the minimum change in x (i.e., $(\Delta x)_t = |x_t - x^o_{t-1}|$) at time t that will effect a change in the observable outcome of the decision. Note that $(\Delta x)_t$ is that minimum change in x (we are implicitly assuming that decision parameter y remains constant; i.e., $y_t = y^o_{t-1} = y^o$) that will produce a change in the production level $(\Delta q)_t$ at time t that is greater than or equal to the minimum profitable change $(\Delta q)^*_t$. Hence, the x_t-informon $(\Delta x)^*_t$ is given by $(\Delta x)^*_t = |x_t - x^o_{t-1}|$ where x_t is the minimum value of x for which $|q_t - q^o_{t-1}| \geq (\Delta q)^*_t$. (Note that $|q_t - q^o_{t-1}| = |f(x_t, y^o) - f(x^o_{t-1}, y^o)|$ if the DM is using the predictive model described by $f(x_t, y_t)$ and $|q_t - q^o_{t-1}| = |g(x_t, y^o) - g(x^o_{t-1}, y^o)|$ if he is using a different model described by $g(x_t, y_t)$.) Consequently, with respect to the decision parameter x_t, a quantitative measure of information has been established. Note that the fundamental quantum of information which has been called the informon is both situation-dependent (it depends upon the decision process) and time-dependent. The time-dependence of the informon stems from the fact that the so-called minimum profitable change $(\Delta q)^*_t$ is time-dependent; this is mainly due to the fact that it is unlikely that the set-up costs incurred when changing the production level from 5 to 15 are identical to those incurred when changing the level from say 105 to 115, although the amount of change is the same.

In terms of the decision parameter x_t, the amount of information (Φ) contained in a data set S which will yield a change in the parameter value of $(\Delta x)_t = |x_t - x^o_{t-1}|$ at time t is given by

$$\Phi_{x_t}[S(\Delta x)_t] = \begin{cases} 0 \text{ if } (\Delta x)_t < (\Delta x)^*_t \\ \dfrac{(\Delta x)_t}{(\Delta x)^*_t} \quad \text{if } (\Delta x)_t \geq (\Delta x)^*_t \end{cases}$$

where $(\Delta x)_t$ is the value of the x-informon at time t.

Again, it is significant to note that the amount of information in a data set has been defined so that it is both time-dependent and situation-dependent. The important point is that information can be defined in a relative way rather than in the absolute way in which it is defined in communication theory.

An analysis for the decision parameter y_t would parallel the above analysis for x_t.

Consider the following examples:

Example 1

given: $q_t = 2x_t + 5y_t + 6$

$(\Delta q)^*_t = 3$ for all t

$x^o_{t-1} = 5$, $y^o_{t-1} = 3$ so that $q^o_{t-1} = 31$

then: the x_t-informon is given by $\frac{(\Delta x)^*_t}{2} = {}^3/_2$;

the y_t-informon is given by $(\Delta y)^*_t = \frac{(\Delta q)^*_t}{5} = {}^3/_5$

Given a data set S that will produce a change in x_t given by $(\Delta x)_t = 10$, then the amount of information contained in this data at time t is

$$\Phi_{x_t}\ [S(\Delta x)_t] = \frac{10}{(\Delta x)^*_t} = \frac{10}{(3/2)} = 6^2/_3 \ \ x_t\text{-informons.}$$

Example 2

given: $q_t = f(x_t,y_t) = x_t^2 + 2x_ty_t + 3y_t^2 + 4x_t + 5y_t + 6$

$(\Delta q)^*_t = h(q_{t-1}) = .01q_{t-1} + 5$

$x^o_{t-1} = 9$, $y^o_{t-1} = 10$.

What is the x_t-informon?

$q_{t-1} = f(x_{t-1}, y_{t-1}) = f(9,10) = 653$

$(\Delta q)^*_t = h(653) = 11.53$

$|f(x_t,y^o) - f(x^o_{t-1}, y^o)| \geq (\Delta q)^*_t$ implies that

$x_t^2 + 24x_t - 308.53 \geq 0$

Solving the equality yields two roots for x_t: 9.25 and -33.25.

Hence, the x_t-informon is given by

$$(\Delta x)^*_t = \min(|9.25-9|,\ \ |-33.25-9|) = .25.$$

This value implies that any piece of data that indicates a minimum change of .25 in the value of the decision parameter x_t for the t^{th} production period will effect a change in the observable outcome.

A similar analysis for y_t indicates that the y_t-informon is given by $(\Delta y)^*_t = \min(|10.07-10|,\ |-17.73-10|) = .07$. Hence, any piece of data that will change the value of y_t by .07 or more is, in a sense, "relevant" at time t.

Given a data set S that will produce a change in x given by $(\Delta x)_t = 10$, then the amount of information contained in this data set at time t is

$$\Phi_{x_t}\ [S(\Delta x)_t] = \frac{10}{(\Delta x)^*_t} = \frac{10}{.25} = 40\ x_t\text{-informons.}$$

For a given decision opportunity and for a given situation (i.e., a given predictive model-decision rule configuration), it is possible to notationally represent the pertinent informons by a column vector which we may call the <u>informon vector</u>:

$$\begin{bmatrix} (\Delta x)^*_t \\ (\Delta y)^*_t \end{bmatrix}$$

If we consider a finite planning horizon of m periods and a situation with n decision parameters, then for a given predictive model-decision rule configuration we have an n x m <u>informon matrix</u>:

		DECISION OPPORTUNITIES (t)			
		1	2	...	m
	x_1	$(\Delta x_1)^*_1$	$(\Delta x_1)^*_2$	...	$(\Delta x_1)^*_m$
	x_2	$(\Delta x_2)^*_1$	$(\Delta x_2)^*_2$	...	$(\Delta x_2)^*_m$
	.	.	.		.
	.	.	.		.
DECISION PARAMETERS	.	.	.		.
(x_i)	x_n	$(\Delta x_n)^*_1$	$(\Delta x_n)^*_2$		$(\Delta x_n)^*_m$

Before proceeding to the analysis of a precise example of such a decision system as has been discussed, it may be worthwhile to pause and take note of the following points:

1. "information" has been tied to a measurable set of observable outcomes and can, therefore, be measured in terms of physical quantities;
2. "information" has been implicitly defined in a generalized and relative (time-dependent and situation-dependent) manner;
3. the amount of information contained in a data set has been defined;
4. an informon or quantum of information has been specified;
5. the value or relevance (in terms of informons) of information with respect to a given decision has been implied;
6. a notationally convenient method of representing the informons in a dynamic decision-making situation has been suggested.

3. A PRECISE DESCRIPTION OF THE MODEL USED

In order to gain a better understanding of the concepts discussed in the last section, a specific example, from which numerical data can be generated, will now be formulated by defining a set of arbitrary functional relationships among a set of hypothetical parameters that might be involved in a production control problem.

Suppose that the external economic environment space is a Cartesian product set D x S, where D is the set of all possible states of the Dow-Jones Average (where a "state" is the actual average rounded to the nearest 25 points) and S is the set of all possible states of the sales price of the firm's stock (where a "state" is the price rounded to the nearest $5). Furthermore, if the Dow-Jones Average and the stock sales price at decision opportunity t-1 are known to be d_{t-1} and s_{t-1} respectively, then it will be assumed that the state transitions between time t-1 and time t occur according to the following transition functions:

$$d_t = \begin{cases} d_{t-1} -50 \text{ points with probability} & .05 \\ d_{t-1} -25 \text{ points with probability} & .20 \\ d_{t-1} \quad\ \text{ points with probability} & .50 \\ d_{t-1} +25 \text{ points with probability} & .20 \\ d_{t-1} +05 \text{ points with probability} & .05 \end{cases}$$

$$s_t = \begin{cases} s_{t-1} -10 \text{ dollars with probability} & .10 \\ s_{t-1} - 5 \text{ dollars with probability} & .25 \\ s_{t-1} \quad\ \text{ dollars with probability} & .30 \\ s_{t-1} + 5 \text{ dollars with probability} & .25 \\ s_{t-1} +10 \text{ dollars with probability} & .10 \end{cases}$$

Also, the environment space information structure $I_y: DxS \rightarrow Y$ maps these basically uncontrollable external environmental parameters onto a signal $y_t \varepsilon Y$ according to the function

$$I_y(d_t, s_t) = d_t/100 + s_t/10 = y_t.$$

Looking now to the result space, suppose that this space is a Cartesian product IxRxL where I, R, and L are the sets consisting of all possible inventory levels, raw materials levels, and labor available levels respectively. The elements $(i_t, r_t, l_t) \varepsilon$ IxRxL of this Cartesian product set are controllable in the sense that each depends on and is determined by the action taken at the last decision opportunity:

$$i_t = i_{t-1} + .20\ (\Delta q)_{t-1}$$

$$r_t = r_{t-1} - q_{t-1} - (\Delta q)_{t-1} + 475$$

$$l_t = l_{t-1} + .40\ (\Delta q)_{t-1}$$

Furthermore, assume that the result space information structure $I_x: IxRxL \rightarrow X$ is defined by

$$I_x(i_t, r_t, l_t) = .4i_t + .084r_t + .2(l_t) = x_t$$

Notice that both information structures I_x and I_y have been defined deterministically so that both infallibly emit the same signal each time the same set of input conditions occur.

The decision maker (DM), upon receiving the emitted signals x_t and y_t utilizes his predictive model to determine the exact level at which the firm should produce during production period t. Initially, it will be assumed that the DM's predictive model is defined by the production function

$$f(x_t, y_t) = 3x_t + 10y_t = q_t.$$

If there is to be a means of evaluating and comparing alternatives, the firm's payoff function must be specified. The firm will be assumed to be a utility maximizer. The utility function U is a function of the decision "outcome" (in the classical decision theoretic sense of the word), which is, in turn, a function of the course of action (i.e., the desired change in production $(\Delta q)_t$) selected by the DM and the state of nature (as reflected by the changes in the parameters d, s, i, r, and l). The exact form of the utility function U and its derivation are given in the Appendix.

Incidently, although the precise form of the utility function is arbitrary in this case, the function was formulated so that the firm will be proportionately rewarded for taking those actions which intuitively seem favorable in view of the possible changes in the environmental parameters. For example, an increase in production in view of a substantial rise in the Dow Jones Average would be rewarded in proportion to the magnitude of the increase while a decision to decrease production would be similarly penalized. All environmental changes must be considered together of course, to determine the ultimate utility of a given decision. The scale factors provide that a maximally favorable outcome will be reflected by a utility of 1.0 while a maximally unfavorable outcome will be indicated by a utility of -1.0.

Now, if the minimum profitable change is assumed to be 2%, the action decided upon via the decision rule is either to alter the production level during the t^{th} period by $(\Delta q)_t = q_t - q_{t-1}$ (if $(\Delta q)_t \geq (\Delta q)^*_t = .02q_{t-1}$) or to maintain the same production level (if $(\Delta q)_t < (\Delta q)^*_t = .02q_{t-1}$). Notice that, in accordance with the definition of an informon for each decision parameter, one x_t-informon at time t is $\frac{(\Delta q)^*_t}{3}$ and one y_t-informon at time t is $\frac{(\Delta q)^*_t}{10}$. Again the "situation-dependence" of the informon is emphasized.

4. EXPERIMENTATION

Now that a precise mathematical description of the production control decision system under consideration has been given, the specification of starting conditions at time zero will initialize this dynamic decision-making system.

Since the hypothetical production control system described thus far has been postulated with knowledge of the fact that a simulation of the system is to serve as the "real world" in which the study is to be conducted[3], it is readily apparent that it is possible to construct such a simulation that represents the system with perfect accuracy. The simulation in question was written in FORTRAN IV and, in its most basic form, consisted of approximately 150 FORTRAN statements. As each of the experiments to be discussed was performed, the basic simulation was enriched modularly.

Before commencing the discussion, it should be made clear that the purpose of the experimentation and the resulting model enrichment was not to make the model more operational and/or more applicable to an actual production control environment, but rather the purpose was to investigate the feasibility of maintaining a meaningful quantification of information flow under varied conditions.

It should also be pointed out that each time a change in the basic model was made, the resulting simulation whose results were analyzed to determine the effects of this change consisted of 25 three-year periods in the life of the firm (where the production period was taken to be one

[3] See the comments in the Introduction regarding the role of simulation in this study for further clarification.

month). Hence, any figures given in this section were arrived at by analyzing the results of sensitivity analyses. It is believed that sufficient care was taken to insure that starting conditions and operating functions, conditions, parameters, etc. (except that parameter being analyzed, of course), were identical. Consequently, although it has been indicated that the purpose of experimentation in this case is, in a sense, more qualitative than quantitative, any figures given are the results of carefully controlled sensitivity analyses.

4.1 An Alternate Predictive Model

In section 1.2 it was noted that the decision maker (i.e., the production manager) may well have an alternative conception about how the input parameters or "signals" he receives are related to that production level that he predicts will prove to be optimal. More precisely, the DM may have an alternate predictive model; an alternate production function $g:XxY \to Q$ would represent such a model.

If g is defined by

$$g(x_t, y_t) = 2x_t + 12y_t = q_t,$$

the DM now has available two different production functions which can be used to generate the predicted optimal production level q_t. At a given decision opportunity, only one such model may be utilized. However, for a set of decision opportunities, the DM may, according to some predefined strategy, utilize both models at different points in time.

The quantification of information flow described in section 2 explicitly points out the "situation-dependence" of the value of that fundamental quantum of information called the "informon". Hence, the exact value of the informon at a given decision-making opportunity is a function of the decision process in question (recall that the informon is time-dependent, too, however). Consequently, if predictive model G (i.e., the model described by the production function $g(x_t,y_t) = q_t$ is used, the value of the informon for a given decision parameter at a given decision opportunity will, in general, differ from the value of the informon under predictive model F. (Predictive model F is that model described by the production function $f(x_t,y_t) = q_t$, as defined in Section 3.)

The results of two simulation runs, in each of which the DM utilized either predictive model F or predictive model G exclusively, indicated that predictive model F was superior to predictive model G in that it resulted in a significantly greater utility yield to the firm on the average. Furthermore, the imposition of an arbitrary "mixed strategy" (whereby the DM uses at time t that predictive model which either did or would have generated the more favorable production level at time t-1) by which the DM could use either of the two predictive models resulted in a substantially more favorable outcome to the firm than either of the "pure strategies" discussed above. Although it is of only minor significance here, the exact results of the three runs are reflected by the following: (a) using predictive model F exclusively, the DM gained an average utility per decision opportunity of .09 "utiles"; (b) using model G exclusively, the DM lost .05 utiles per decision opportunity; (c) using the mixed strategy, the DM realized an average gain of .38 utiles per decision opportunity.

The significance of this particular experiment lies in the fact that a precise and meaningful quantification of information flow was maintained in this situation where the production manager had an alternate production function available.

4.2 The Addition of Uncontrollable External Environmental Intervention to the Execution (E_x) Function[4]

Until now it has been tacitly assumed that the desired course of action selected by the DM is perfectly transformed into an observable outcome (i.e., the Execution component has been interpreted as an identity mapping with no uncertainty attached). Since it is often the case that the actual implementation of a desired course of action may, in fact, be less than "perfect" and less than "certain", a stochastic routine was incorporated whereby uncontrollable external environmental perturbations (e.g., power failure, strike, etc.) sometimes intervened to prevent complete and/or perfect implementation of a desired course of action.

As a result of this addition, the more realistic situation arises in which the DM (or the firm) is rewarded or punished not for the course of action decided upon, but for that part of the desired course of action that was actually implemented or for the degree to which the desired course of action was "executed".

The occurrence of this uncontrollable intervention has certain ramifications which affect the setting in which the subsequent decision opportunity occurs. (Only a first-order effect is assumed at this point.) Specifically, the occurrence of this event affects the subsequent state of the result space R in that it affects the inventory level (i), the raw materials level (r), and the labor available (l).[5]

Intuitively, one would expect that the transformed data generated

[4]Section 4.5 further refines this enrichment of the model and deals with it in a slightly different context.

[5]Refer to Section 3.

after such an uncontrollable environmental intervention occurred might contain more information with respect to the subsequent decision opportunity than would be the case had the intervention not occurred. Analysis of the pertinent simulation results revealed that this was generally the case. The principal reason for this phenomenon is simply that because of the intervention the production level is likely to differ more from that level believed to be optimal than it would had the intervention not occurred. Consequently, since the fundamental unit of information has been defined in terms of potential effects on the observable outcome of a decision, the DM, if he is to act in a corrective manner, is likely to have an increased number of informons available in the data set including the transformed data. (The implications of these concepts are discussed further in Section 4.5).

It is clear that the addition of this uncontrollable environmental intervention routine into the Execution component does perturb the whole production control system and that the exact nature of this perturbation is reflected in a precise manner by the quantified information flow.

4.3 The Addition of Dynamic Adjustment Capabilities to the Decision Maker's Predictive Model

After a decision has been made to alter the production level by a given amount and after the action has been executed, the firm then receives a "payoff" -- the utility associated with the executed action in view of the now-known state of nature. Once this true state of nature is known, the DM can determine, in retrospect, that optimal change in production (Δq_{opt}) that would have maximized the payoff under this state of nature. Basically, the dynamic routine added to the simulation allows the DM to determine Δq_{opt} after the fact (i.e., after he knows the outcome of the decision he made based on his interpretation of the then-unknown state of nature). Then the DM can dynamically adjust the coefficients which describe his predictive model so that if similar input conditions occur at a subsequent decision opportunity, the DM is likely to act in a manner that will yield a greater payoff.

To incorporate this dynamic routine for a given predictive model, it was necessary to impose an additional constraint on the system. To prevent the contingency in which the dynamic adjustment process might determine that the optimal production change would have been excessively large, it proved advantageous to put a ceiling on the allowable production change. Hence, as well as the Minimum Profitable Change of 2% (as discussed in sections 2 and 3), it was arbitrarily assumed that the Maximum Profitable Change is 15%. This constraint, or a similar one, does not seem unrealistic from a production systems point of view.

For a single predictive model, the quantified information flow was changed by the addition of this dynamic adjustment routine only in that the predictive model coefficients, as used in the determination of the informon for each decision parameter, became time-dependent variables. Rather than creating a problem in the quantification, however, this phenomenon merely serves to further emphasize the time-dependence of the informon as previously discussed (see Section 2).

Testing the decision system with the dynamic adjustment routine and comparing the payoffs received with those received from the system without the routine, it was found that, on the average, the dynamic adjustment capability permitted the firm to realize a 65% increase in payoffs received.

4.4 The Addition of a New Information Source

Up to this point it has been assumed that all of the potential information sources that are pertinent to the production decision system are known. The resulting quantification of information flow has then been based on the degree to which information derived from these sources affects or is capable of affecting the outcomes of production decisions. With respect to the quantification established on these bases, it is reasonable to ask if this quantification will remain meaningful if a new information source is introduced and/or discovered. To investigate this possibility, a new information source was hypothesized and injected into the system.

Previously the firm in question has made its production decisions independent of any competitor. Now, however, for the sake of giving the proposed new information source a name, it will be assumed that the firm discovered that it must in some way "react" to the competition (e.g., if the market situation is duopolistic, the firm must shift from the "leader" role to the "follower" role so that the production level will be, in part, a function of the competitor's behavior). At any rate, it will be assumed that the pertinent behavior of the competition that could potentially affect the firm's production decision at decision opportunity t is reflected by a competition index c_t.

The basic dichotomy, established previously between information sources which are external to the firm (i.e., "subclasses" of the external economic environment space E) and those which are internal to the firm (i.e., "subclasses" of the result space R) permits the new information source to be classified as an obvious external source. With this in mind, the information structure I_y which maps elements of E into the signal space Y can now be thought of as being a function of d_t, s_t, and c_y instead of just d_t and s_t as before.[6]

The establishment of arbitrary relationships for both a stochastic transition function for c_t and the effect of c_t on the external economic environment signal y_t (via the information structure I_y) allowed this new information source to be incorporated into the system model.

Experimental results indicated, as is obvious, that the new information source changed the amount of information available at a given decision opportunity. However, it is less obvious and more significant to note that the way in which this quantity of information was determined remained unchanged. Specifically, the determination of the fundamental quantum of information (the informon) for a given decision opportunity depends on only the known information sources (or the effects information from these sources is known to have in terms of potentially altering the production decision outcome) and is unaffected by the presences of new information; the exact number of quanta present at that same decision opportunity will, however, reflect the presence of the new information.

In view of the above comments, it can be seen that the basic framework given previously (principally in Section 2) for quantifying the information flow in this system does permit the influx of new information. Furthermore, this framework is capable of dealing with this new information in a meaningful, quantitative manner without the necessity of redefining those basic formulations which actually define the quantification process.

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[6]See Sections 1.1 and 3 for a more complete discussion of the relationships previously established among these parameters.

4.5 Dealing with the Effects of Executional Uncertainty

In section 4.2 the source of uncertainty concerning the Execution function (E_x) was an arbitrary but known stochastic routine which resulted in an uncontrollable environmental intervention which sometimes perturbed the execution of a desired course of action. Although this perturbation was made known to the decision maker (DM) via feedback, it was implicitly assumed that the DM did not really utilize this data in any meaningful way except to adjust his interpretation of the subsequent state of nature.

At this point a stochastic, but unpredictable, routine was added to the model which simulates limited uncertainty in the Execution function (whereas before the routine simulated risk; i.e., the probability distribution of the "states of intervention" was known). Furthermore, the DM, although unable to predict explicitly beforehand when the uncontrollable intervention would occur, is informed via feedback, after a time lag of one production period, that intervention did occur (i.e., a binary signal), and, after a time lag of two production periods, the exact amount of the intervention or perturbation. Specifically, the fact that an uncontrollable perturbation in the execution of a desired production change occurred at time t is made known to the DM at time t + 1, but the exact amount of the perturbation is assumed to be unknown until time t + 2. Hence, the DM, required to respond to the perturbation in a corrective manner at time t + 1, can only make a prediction about the exact amount of the perturbation.

To allow the DM to function in this "uncertain situation", a memory element has been added to the decision-making function. Specifically, the DM, when required to take corrective action at time t + 1 concerning a perturbation of an unknown degree that occurred at time t, can "remember" the past perturbations that have occurred and can therefore "predict" that the perburbation at time t was the arithmetic mean of those past perturbations. At time t + 2 the DM can then update his memory element by recording the exact degree of perturbation that actually occurred at time t. Furthermore, the DM can then input this information into the routine which dynamically adjusts his predictive model.[7]

The uncontrollable intervention discussed above was allowed to perturb a desired production change at an arbitrary 20% of the time. The exact amount of perturbation was a random percentage of the desired change. It seems doubtful that, in a realistic sense, the production level would be uncontrollably increased by external intervention--hence, the justification for a percentage decrease. Of course, it must be pointed out that a "ramdom percentage decrease" actually implies a uniform distribution and, as such, definitely connotes risk (rather than uncertainty, as mentioned previously) from the viewpoint of one outside the system. However, since this property is now known by the DM (unless a "very large number" of decision opportunities are considered -- in which case the operation of the memory element would allow the DM to "learn" the mean of this uniform distribution as he closed in on a standard corrective response of (.50) times the previously desired production change), it is argued that the DM is functioning under conditions of limited uncertainty with respect to the execution function.

In regard to the experiment concerning this feature of the model, two specific sensitivity analyses were performed. The purpose of the first was to measure the effect in terms of utility of the corrective action taken via the functioning of the memory element exclusive of the dynamic

[7]This routine is described in Section 4.3.

adjustment process; the purpose of the second analysis was to measure the same affect coupled with the dynamic adjustment process. The results of the first analysis showed that the corrective action increased the utility gained by the firm in a three-year period by an average of 0.38%; the results of the second analysis showed an average gain in utility of 0.77% per three-year period. The conclusion is that this feature, an obvious enrichment in the overall decision model, is a vital contributor to the firm's goal in that it results in a greater return in terms of utility.

5. RESULTS OF THE SIMULATION

A specific dynamic decision-making problem cast in a management information environment has been posed, elaborated upon, simulated, and analyzed in some detail. The following characteristics are inherent in the structure of this decision system:

a) multiple stochastic inputs including both uncontrollable and controllable parameters;
b) alternate predictive models are available to the DM;
c) although the DM is restricted to one decision rule, the number of different courses of action that can result from the predictive model-decision rule configuration is countably infinite;
d) uncontrollable environmental fluctuations may prevent the desired course of action from being implemented;
e) certain second-order feedback features have been added to permit the system to possess dynamic adaptability characteristics;
f) multiple observable actions result from the action taken at each decision opportunity.

In this limited problem setting, several important results have been achieved.

Information has been defined in a relative (time-dependent and situation-dependent) manner; the definition is broader and seemingly more useful than the absolute, context-free definition posed in communication thoery. In accordance with the concepts discussed by Yovits and Ernst (Reference 5), information is "data of value in decision making" --that is, data that are of some useful resource in the decision-making problem at hand. Furthermore, a method of determining the amount of information contained in this identical data set may be sharply reduced or even nil. Also, that data which may be of value in one decision-making situation may be of no consequence whatever in another decision-making situation; hence, even at the same point in time, two identical data sets may not contain the same amount of information. It is argued that this relative way of defining information is considerably more useful than the engineering-aspects-only approach taken in communication theory.

A precise quantification of the flow of information through a decision-making system has been achieved and a quantitative analysis of the interrelationship of information and decision making for a given problem has been performed.

In the simulation the variable TQUANT is the arithmetic sum at time t of the number of x_t-informons and the number of y_t-informons (i.e., TQUANT is the number of "total informons" available to the decision maker at time t as a result of the changes of both the decision parameters x_t and y_t). Clearly, if either x_t or y_t remained constant, a meaningful quantitative analysis of the relationship between the actual decision making and information could be performed examining only YQUANT (the number of y_t-informons contained in the disseminated signal y_t) or XQUANT (the number of x_y-informons contained in the disseminated signal x_t) respectively. However, as the many trials of the simulation concur, this is rarely the case so that some sort of composition of all the pertinent informons must be examined: in this case that composition is the value indicated by TQUANT. (Note that it is highly doubtful that the simple arithmetic sum of the informons of all the decision parameters will generally yield a meaningful correlative index between information and decision making as, it will be shown, it does in this instance. Almost certainly this particular form of TQUANT is a result of the linear functions (e.g., $q_t = f(x_t, y_t)$ used to describe the system.)

Referring now to the sample 36-month simulation given in Table 1, notice that the decision process results in a change of the production level (i.e., DELTQ $\neq$ 0.0) <u>if and only if</u> $|\text{TQUANT}| \geq 1$; this occurs only at months 5, 10, 13, 16, 19, 24, 26, 27, 34, and 36. (This relationship holds true for a whole series of simulations performed using only predictive model F (i.e., before the problem setting was enriched by the introduction of a alternative predictive model). Thereafter, the correlation is imperfect whenever the DM changes predictive models; this is clearly the result of "situation-dependence" of the informons and simply indicates that a more sophisticated function need be developed for finding TQUANT in such a way as to restore the perfect correlation discussed at the beginning of this paragraph.) Furthermore, this phenomenon is perfectly consistent with the definition of an informon; that is, whenever $|\text{TQUANT}| > 1$, the information that generated this value contains no "total-informons" in the sense that no action to change the production level will result. Hence, although the presence of information is indicated by any non-zero value of TQUANT, the information is relevant or of value (i.e., it will affect the course of action selected) when (and only when) $|\text{TQUANT}| \geq 1$, since only then does the composition of all the information contain at least one "total-informon."

Also note that the degree of relevance among those sets of information generating values of TQUANT whose absolute values are greater than or equal to one is indicated. For instance, during months 24 and 36 the values of TQUANT are 1.84 and 1.22 respectively. The information that generated the value of TQUANT of 1.84 was more relevant or of more

T	QOLD	MPG	D	S	Y	DELTY	YSTAR	YQUANT	I	R	L	X	DELTX	XSTAR	XQUANT	TQUANT	PREDQ	LEVEL	DELTQ
1	469	9.4	700	100	17.00	0.0	0.94	0.0	50	480	200	100.35	0.45	3.13	0.14	0.14	471.0	469	0.
2	469	9.4	725	100	17.25	0.25	0.94	0.27	50	486	200	100.85	0.95	3.13	0.30	0.57	475.0	469	0.
3	469	9.4	725	100	17.25	0.25	0.94	0.27	50	492	200	101.35	1.45	3.13	0.46	0.73	476.6	469	0.
4	469	9.4	750	95	17.00	0.0	0.94	0.0	50	498	200	101.86	1.96	3.13	0.63	0.63	475.6	469	0.
5	469	9.4	750	100	17.50	0.50	0.94	0.53	50	504	200	102.36	2.46	3.13	0.79	1.32	482.1	482	13.
6	482	9.6	775	105	18.25	0.75	0.96	0.78	52	484	205	102.76	0.40	3.21	0.12	0.90	490.8	482	0.
7	482	9.6	750	100	17.50	0.0	0.96	0.0	52	477	205	102.17	-0.19	3.21	-0.06	-0.06	481.5	482	0.
8	482	9.6	700	105	17.50	0.0	0.96	0.0	52	470	205	101.59	-0.78	3.21	-0.24	-0.24	479.8	482	0.
9	482	9.6	750	105	18.00	0.50	0.96	0.52	52	463	205	101.00	-1.36	3.21	-0.42	0.09	483.0	482	0.
10	482	9.6	775	115	19.25	1.75	0.96	1.82	52	456	205	100.41	-1.95	3.21	-0.61	1.21	493.7	494	12.
11	494	9.9	775	110	18.75	-0.50	0.99	-0.51	54	425	209	99.73	-0.68	3.29	-0.21	-0.71	486.7	494	0.
12	494	9.9	750	115	19.00	-0.25	0.99	-0.25	54	406	209	98.13	-2.28	3.29	-0.69	-0.95	484.4	494	0.
13	494	9.9	750	115	19.00	-0.25	0.99	-0.25	54	387	209	96.53	-3.88	3.29	-1.18	-1.43	479.6	480	-13.
14	480	9.6	725	115	18.75	-0.25	0.96	-0.26	52	395	204	95.13	-1.41	3.20	-0.44	-0.70	472.9	480	0.
15	480	9.6	700	120	19.00	0.0	0.96	0.0	52	390	204	94.71	-1.83	3.20	-0.57	-0.57	474.1	480	0.
16	480	9.6	700	115	18.50	-0.50	0.96	-0.52	52	385	204	94.29	-2.25	3.20	-0.70	-1.22	467.9	468	-11.
17	468	9.4	675	125	19.25	0.75	0.94	0.80	50	403	200	94.04	-0.25	3.12	-0.08	0.72	474.6	468	0.
18	468	9.4	675	115	18.25	-0.25	0.94	-0.27	50	410	200	94.63	0.34	3.12	0.11	-0.16	466.4	468	0.
19	468	9.4	625	110	17.25	-1.25	0.94	-1.34	50	417	200	95.21	0.93	3.12	0.30	-1.04	458.1	458	-9.
20	458	9.2	625	105	16.25	-0.50	0.92	-0.55	48	443	196	95.96	0.74	3.05	0.24	-0.30	455.4	458	0.
21	458	9.2	625	110	17.25	0.0	0.92	0.0	48	460	196	97.39	2.17	3.05	0.71	0.71	464.7	458	0.
22	458	9.2	600	110	17.00	-0.25	0.92	-0.27	48	477	196	98.81	3.60	3.05	1.18	0.91	466.4	458	0.
23	458	9.2	550	105	16.00	-1.25	0.92	-1.36	48	494	196	100.24	5.03	3.05	1.65	0.28	460.7	458	0.
24	458	9.2	550	115	17.00	-0.25	0.92	-0.27	48	511	196	101.67	6.46	3.05	2.11	1.84	475.0	475	17.
25	475	9.5	575	110	16.75	-0.25	0.95	-0.26	51	494	203	102.96	1.29	3.17	0.41	0.14	476.4	475	0.
26	475	9.5	625	120	18.25	1.25	0.95	1.32	51	494	203	102.96	1.29	3.17	0.41	1.72	491.4	491	16.
27	491	9.8	575	115	17.25	-1.00	0.98	-1.02	54	462	209	102.83	-0.13	3.27	-0.04	-1.06	481.0	481	-9.
28	481	9.6	575	120	17.75	0.50	0.96	0.52	53	465	206	101.65	-1.19	3.21	-0.37	0.15	482.4	481	0.
29	481	9.6	575	115	17.25	0.0	0.96	0.0	53	459	206	101.14	-1.69	3.21	-0.53	-0.53	475.9	481	0.
30	481	9.6	600	115	17.50	0.25	0.96	0.26	53	453	206	100.64	-2.20	3.21	-0.68	-0.42	476.9	481	0.
31	481	9.6	625	120	18.25	1.00	0.96	1.04	53	447	206	100.13	-2.70	3.21	-0.84	0.20	482.9	481	0.
32	481	9.6	625	120	18.25	1.00	0.96	1.04	53	441	206	99.63	-3.20	3.21	-1.00	0.04	481.4	481	0.
33	481	9.6	625	115	17.75	0.50	0.96	0.52	53	435	206	99.13	-3.71	3.21	-1.16	-0.64	474.9	481	0.
34	481	9.6	600	110	17.00	-0.25	0.96	-0.26	53	429	206	98.62	-4.21	3.21	-1.31	-1.57	465.9	466	-14.
35	466	9.3	600	115	17.50	0.50	0.93	0.54	50	452	200	98.31	-0.31	3.11	-0.10	0.44	469.9	466	0.
36	466	9.3	600	120	18.00	1.00	0.93	1.07	50	461	200	99.07	0.45	3.11	0.14	1.22	477.2	477	11.

TABLE 1.

value during month 24 than was the information that generated TQUANT = 1.22 during month 36 since the former resulted in a production level change of +17 while the latter resulted in a change of only +11. Notice, however, that such a comparison of sets of information defined at different points in time is of little or no real value in view of the time-dependent definition of information posed. A comparison of different sets of information defined during the same time frame would certainly be of merit; such a comparison is possible in this case by examining XQUANT and YQUANT. For example, consider month 32 of the sample trial given in Table 1. Which of the following data sets contains <u>more relevant information</u>?

Set I: the Dow-Jones Average is 625 points; the market price of the firm's stock is 120 dollars.

Set II: the inventory level is 53; the amount of raw materials available is 441; the amount of labor available is 206 men.

The fact that XQUANT is -1.00 (the sign indicates only the direction in which production would be affected by this information) while YQUANT is +1.04 indicates that Set I contains slightly more relevant information.

Notice that during month 26 the Dow-Jones Average and the market price of the stock are identical to those of month 32. Hence, the <u>data content</u> of these sets during months 26 and 32 are identical. However, since YQUANT is +1.32 during month 26 and +1.04 during month 32, the <u>information content</u> of identical data is clearly not the same. The time-dependence of information is again emphasized.

It becomes clear that defining "information" and "a quantum of information" as has been done facilitates a significant and useful quantitative analysis of the interrelationship of information and decision making.

Incidently, Table 1 also contains 36 "informon vectors" (at time t, the values of XSTAR and YSTAR are the x_t-informon and the y_t-informon respectively); taken together these 36 vectors comprise the "informon matrix" for the 36-month dynamic decision-making situation in question. Hence, the notationally convenient matrix representation of the various informons, as outlined previously in Section 2 has been achieved in the simulation.

6. SOME GENERAL IMPLICATIONS OF THE STUDY

A good deal of the contemporary literature on information systems contains authoritative opinions about those areas toward which research efforts should be directed. The purpose of this concluding section is to point out some of these areas and to draw any possible correlations between these needs and the implications of the approaches taken in this study.

6.1 Toward an Integration of Information and Decision Making

A description of the management information system research program contained in a report to the National Science Foundation (10) states: "... the program is concerned with the identification and formulation of information requirements for decision making and the relationship between these two important areas." Certainly the rather precise description of this interrelationship given for the particular decision-making situation discussed in this paper would seem to offer a viable avenue of approach. Both the conceptual description of information as the key resource or "input" for a decision process and the precise quantitative analysis contained in the simulation would seem to be of value.

With respect to the quantitative analysis, it is significant to note that the need for the development of refined measures of information content and information flow in a management information environment has been cited (9): Davidson and Trueblood (4) also make note of the need for an integration of the concepts of information and decision making when they advise the accounting faction to concern itself with integrating information flows with decision centers and decision requirements.

6.2 On the Structure of this Model in a Management Information Environment

With respect to the structure or overall conceptualization of the particular model discussed in this paper, it is of interest to note that almost all of contemporary MIS literature offers support to the conceptual components present. To be accurate, of course, it must be re-emphasized that the model discussed in this paper was cast in the conceptual framework of the generalized information system model proposed by Yovits and Ernst (8). The structure offered by this model contains the three basic components that should be, it would seem the basic skeleton of a management information system:

(1) The Information Acquisition and Dissemination component (IAD). This component is the integral part of an MIS that is often loosely referred to as "the information system." The role of this component is paramount, well-accepted, and, it would seem, needs little or no justification.

(2) The Decision Making/Maker component (DM). Allusions have already been made to the fruitfulness that can be achieved by approaching the problem of information transfer from a decision-oriented point of view. References (1) through (4) and (8) all clearly state that the need for approaching MIS development in this way.

(3) The Transformation component (T). This component makes explicit the feedback relationship that must be present in a control system configuration. The cornerstone assertion of industrial dynamics, that organizations are most effectively

viewed and managed from a control system perspective (7), would seem to justify the need for such a component in a decision-oriented MIS. In Reference (1) Ackoff supplements this by commenting, "Information systems are subsystems of control systems. They cannot be designed adequately without taking control into account." Furthermore, it is clear that if an MIS is to possess the dynamic characteristics of flexibility, adaptivity, and adjustability, then the role of the control or "transformation" component is certainly significant.

Roberts (7) cites a need for integrating all three of the above components in a system concerned with the flow of management information by his assertion that decisions are the controllers of the flow of information between organizational components. Hence, it would seem that the model provides a well-justified framework within which a management decision-making situation can be analyzed.

6.3 IAD Design Implications

Before addressing this question, it might be well to emphasize the critical importance of the need for research developments and endeavors in this area. The Society for Management Information Systems recently published the results of a survey (9), one purpose of which was to rank via "importance ratings" potential MIS research projects. It is of interest to note that out of twenty-six projects listed, the following ranked first: "Development of methods for determining what the content of an information system should be."

At this point it should be clearly stated that any design implications that can be discussed as a result of the work on this model must necessarily be limited to the domain of, at best, rather routine, repetitive type of decisions cast in limited uncertainty conditions. More precisely, the scope of the discussion must be limited (as was the specific model analyzed) to those decision making situations which can be adequately modelled mathematically. Ackoff (1) points out that "one cannot specify what information is required for decision making until an explanatory model of the decision process and the system has been constructed...." And, obviously, the very foundation on which the analysis of the model considered in this paper is based is that the informational requirements for the production control problem in question are precisely specified. At any rate, this critical restriction in the scope of this discussion needs to be clearly understood.

Now consider some of the common deficiencies of information systems today:

Over-information. The DM may have too much irrelevant information available; both cost savings and a less-cluttered decision process would result if the IAD disseminated only "relevant information" (as it is defined in this paper); that is, data must be filtered by the IAD and divested of non-information. Furthermore, only information with more than one "total-informon" need be considered by the DM. When a precise mathematical description of the decision process is possible, this approach certainly seems to have merit with respect to this over-information phenomenon.

Under-information. The DM may have too little relevant information available. It would seem that at the very heart of this deficiency is the problem of inadequate specification of the informational needs for the particular decision at hand. The approach to this problem that seems most feasible at this time is to isolate initially each of the decisions for which the information system is to provide information. A complete analysis of each decision and its informational needs independent of all other decisions would seem to be a viable approach. Then, once these separate information needs are precisely determined, a careful integration and/or synthesis of the individual IAD's that will comprise the information system can be considered in an attempt to eliminate duplications, to reduce cost and effort, and to insure that cost and effort requirements of each IAD is proportionate to the importance of the decision which it serves. While this approach may well be more expensive than others, it may, nonetheless, result in the best possible information configuration being disseminated from each IAD in the information system.

Along this same line it should be noted that once the informational requirements for a given decision are determined, source input/output analysis may be a particularly useful tool in the design of the associated IAD. For instance, having determined the domain of the decision rule, only those data which are in the domain of that particular decision rule need to be collected; all other data collected at that time will be of no value (for that particular decision, that is--hence, the need for a conceptually independent IAD for each decision is implied) and would constitute a waste of time, money, and effort--as would subsequent storage of the "non-informative data."

Untimely information. It would seem that the obvious dilemma here could be substantially alleviated by the formulation of an adequate timeliness-of-information measure of one sort or another. The time dependency of information as it is defined in this paper would certainly appear to be a quantitative and qualitative possibility in this direction.

The joint consideration of both content and timeliness in the procedure used to determine the values of XQUANT, YQUANT, AND TQUANT in the simulation would seem to endow this type of measure with the necessary characteristics.

6.4 Conclusion

Those items discussed in this final section entitled "General Implications of the Study" are recognized to constitute only a portion of those concepts that are in need of research and analysis before truly effective generalized information systems in a management decision-making environment can be developed. Furthermore, the "implications" are largely the result of the analyses performed on a well-defined, hypothetical production control system--clearly not an adequate foundation from which valid generalizations can be inductively extracted. Nonetheless, it would seem that some of the concepts, correlations, and general implications that have been pointed out in this study may well have at least some merit in refining those theoretical bases upon which generalized information systems must be built.

APPENDIX

The Derivation of the Utility Function

The utility function to be discussed is quite arbitrary; the main purpose for its existence lies in its usefulness as a means of comparing the results of various experimental perturbations and additions to the model. Consequently, although an attempt has been made to define this function in a precise and reasonable manner, no claim is made concerning the adherence of the function to, for instance, the rigorous principles governing the formulation of a Von Neumann-Morgenstern utility function. (The degree of variability present in the 5-dimensional "states of nature space" would make such a rigorous formulation extremely difficult and excessively time-consuming in view of the scope of this study.) Nevertheless, it is argued that the utility function derived in this section is suitable for the purpose at hand and that this function was formulated with sufficient initiuitive rigor to exhibit the behavioral characteristics expected of a payoff structure -- i.e., actions which seem intuitively favorable under certain states of nature are rewarded more than less-favorable actions under the same conditions.

The utility associated with the outcome of a given decision is a function of the action taken and the state of nature. Instead of being considered the absolute production change $|(\Delta q)_t|$ or even the directional production change $\pm (\Delta q)_t$, the "action" taken at a given time t is defined as the relative (percent) production change at time t: $\frac{(\Delta q)_t}{q_{t-1}}$. Similarly the 5-triple vector representing the state of nature at time t will consist of the relative changes in the Dow-Jones Average $\left(\frac{(\Delta d)_t}{d_{t-1}}\right)$, the (stock) sales price $\left(\frac{(\Delta s)_t}{s_{t-1}}\right)$, the inventory level $\left(\frac{(\Delta i)_t}{i_{t-1}}\right)$, the raw materials level $\left(\frac{(\Delta r)_t}{r_{t-1}}\right)$, and the labor available $\left(\frac{(\Delta l)_t}{l_{t-1}}\right)$.

In arriving at a feasible utility function of these parameters, each component of the state-of-nature vector was considered separately with the action taken. Hence, essentially five independent utility functional relationships were formulated -- each of which has a range of values on [-1.0, 1.0]. One-fifth of the sum of these components then constituted the composite utility function.

Although the independence assumption is an obvious simplification, it is argued that such an assumption does not taint the information quantification analyses since the entire study is performed in an admittedly hypothetical world.

If the action taken at time t is represented by $B = \frac{(\Delta q)_t}{q_{t-1}}$ (recall that B will never be zero since a zero value, by definition, corresponds to "no action taken"), then the five components of the utility function U are defined by:

$$U, (A_1,B) = \begin{cases} 0, & |A_1| = 0 \\ A_1/2B, & |A_1| \leq |B| \\ 2B/A_1, & |A_1| > |B| \end{cases} \qquad \text{where } A_1 = \frac{(\Delta d)_t}{d_{t-1}}$$

e.g., if the Dow-Jones Average dropped 10%, a production change of -5% would yield a utility of 1.0 whereas a change of +5% would result in a utility of -1.0.

$$U_2\ (A_2,B) = \begin{cases} 0, & |A_2| = 0 \\ A_2/B, & |A_2| \leq |B| \\ B/A_2, & |A_2| > |B| \end{cases} \quad \text{where } A_2 = \frac{(\Delta s)_t}{s_{t-1}}$$

$$U_3\ (A_3,B) = \begin{cases} 0, & |A_3| = 0 \\ -A_3/B & |A_3| \leq |B| \\ -B/A_3 & |A_3| > |B| \end{cases} \quad \text{where } A_3 = \frac{(\Delta i)_t}{i_{t-1}}$$

$$U_4\ (A_4,B) = \begin{cases} 0, & |A_4| = 0 \\ A_4/B & |A_4| \leq |B| \\ B/A_4 & |A_4| > |B| \end{cases} \quad \text{where } A_4 = \frac{(\Delta r)_t}{r_{t-1}}$$

$$U_5\ (A_5,B) = \begin{cases} 0, & |A_5| = 0 \\ 2A_5/3B & |A_5| \leq |B| \\ 3B/2A_5 & |A_5| > |B| \end{cases} \quad \text{where } A_5 = \frac{(\Delta 1)_t}{1_{t-1}}$$

The resulting composite utility function is then given by

$$U(A_1,A_2,A_3,A_4,A_5;B) = \frac{1}{5}\ [U_1,(A_1,B)+ \ldots +U_5(A_5,B)].$$

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